# Assignment 10.3 Step 2 of Final Project

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## Introduction

**Loan is major part of finansial service, where we borrow money from bank and pay it back over the time with monthly or queartly payments. If we cannot pay the money in time, then we are considered as defaulter, I have collected 3 sources of bank data from Kaggle so understand and analize different questions on defaulter.**

## Data Sources and Problem Statement.

```
setwd("C:\\Users\\atanu\\Documents\\BellevueUniversity_MSDS\\DSC520\\Loan Defaulter Data")
default_fin <- read.csv("Default_Fin.csv")
head(default_fin)
```

```
##   Index Employed Bank.Balance Annual.Salary Defaulted.
## 1     1        1      8754.36     532339.56          0
## 2     2        0      9806.16     145273.56          0
## 3     3        1     12882.60     381205.68          0
## 4     4        1      6351.00     428453.88          0
## 5     5        1      9427.92     461562.00          0
## 6     6        0     11035.08      89898.72          0
```

**This data is related to defaulters, this gives individual's information like if the applicant is employed or not, their bank balance annual salary and if the application defaulted.**

```
setwd("C:\\Users\\atanu\\Documents\\BellevueUniversity_MSDS\\DSC520\\Loan Defaulter Data")
loan_data <- read.csv("loan_data.csv")
summary(loan_data)
```

```
##  credit.policy     purpose             int.rate       installment
##  Min.   :0.000   Length:9578        Min.   :0.0600   Min.   : 15.67
##  1st Qu.:1.000   Class :character   1st Qu.:0.1039   1st Qu.:163.77
##  Median :1.000   Mode  :character   Median :0.1221   Median :268.95
##  Mean   :0.805                      Mean   :0.1226   Mean   :319.09
##  3rd Qu.:1.000                      3rd Qu.:0.1407   3rd Qu.:432.76
```

```
##  Max.   :1.000                      Max.   :0.2164   Max.   :940.14
##  log.annual.inc        dti              fico       days.with.cr.line
##  Min.   : 7.548   Min.   : 0.000   Min.   :612.0   Min.   :  179
##  1st Qu.:10.558   1st Qu.: 7.213   1st Qu.:682.0   1st Qu.: 2820
##  Median :10.929   Median :12.665   Median :707.0   Median : 4140
##  Mean   :10.932   Mean   :12.607   Mean   :710.8   Mean   : 4561
##  3rd Qu.:11.291   3rd Qu.:17.950   3rd Qu.:737.0   3rd Qu.: 5730
##  Max.   :14.528   Max.   :29.960   Max.   :827.0   Max.   :17640
##    revol.bal         revol.util    inq.last.6mths    delinq.2yrs
##  Min.   :      0   Min.   :  0.0   Min.   : 0.000   Min.   : 0.0000
##  1st Qu.:   3187   1st Qu.: 22.6   1st Qu.: 0.000   1st Qu.: 0.0000
##  Median :   8596   Median : 46.3   Median : 1.000   Median : 0.0000
##  Mean   :  16914   Mean   : 46.8   Mean   : 1.577   Mean   : 0.1637
##  3rd Qu.:  18250   3rd Qu.: 70.9   3rd Qu.: 2.000   3rd Qu.: 0.0000
##  Max.   :1207359   Max.   :119.0   Max.   :33.000   Max.   :13.0000
##     pub.rec         not.fully.paid
##  Min.   :0.00000   Min.   :0.0000
##  1st Qu.:0.00000   1st Qu.:0.0000
##  Median :0.00000   Median :0.0000
##  Mean   :0.06212   Mean   :0.1601
##  3rd Qu.:0.00000   3rd Qu.:0.0000
##  Max.   :5.00000   Max.   :1.0000
```

**This dataset gives the loan details like the interest rate, fico of the customer, type of the loan, annual income along with fully paid or not flag.**

```
setwd("C:\\Users\\atanu\\Documents\\BellevueUniversity_MSDS\\DSC520\\Loan Defaulter Data")
application_data <- read.csv("application_data.csv")
```

**This data set is about loan application where Target field having 1 means the applicant have difficulty while paying for the loan and also have more than x day late payment.**

**Below are the list of Questions, that we are planning to answer using this data.**

### 1. What attributes affect loan default and what are some major reasons behind it?

### 2. Is there any co-realation between different attributes of loan default data and gereral loan data?

### 3. I think, Income having a direct effect on loan default, because low income could cause default for loan payment. is it true?

### 4. Can I predict if the loan will go to default if I have employment, annual salary and bank balance information?

### 5. Does high fico socre give lower interest retes for loan?.

## Analysis and Implications

```
library(naniar)
miss_var_summary(default_fin)
```

```
## # A tibble: 5 x 3
##   variable      n_miss pct_miss
##   <chr>          <int>    <dbl>
## 1 Index              0        0
## 2 Employed           0        0
## 3 Bank.Balance       0        0
## 4 Annual.Salary      0        0
## 5 Defaulted.         0        0
```

```
miss_var_summary(loan_data)
```

```
## # A tibble: 14 x 3
##    variable          n_miss pct_miss
##    <chr>              <int>    <dbl>
##  1 credit.policy          0        0
##  2 purpose                0        0
##  3 int.rate               0        0
##  4 installment            0        0
##  5 log.annual.inc         0        0
##  6 dti                    0        0
##  7 fico                   0        0
##  8 days.with.cr.line      0        0
##  9 revol.bal              0        0
## 10 revol.util             0        0
## 11 inq.last.6mths         0        0
```

```
## 12 delinq.2yrs           0        0
## 13 pub.rec               0        0
## 14 not.fully.paid        0        0
```

```
miss_var_summary(application_data)
```

```
## # A tibble: 122 x 3
##    variable                 n_miss pct_miss
##    <chr>                     <int>    <dbl>
##  1 COMMONAREA_AVG           214865     69.9
##  2 COMMONAREA_MODE          214865     69.9
##  3 COMMONAREA_MEDI          214865     69.9
##  4 NONLIVINGAPARTMENTS_AVG  213514     69.4
##  5 NONLIVINGAPARTMENTS_MODE 213514     69.4
##  6 NONLIVINGAPARTMENTS_MEDI 213514     69.4
##  7 LIVINGAPARTMENTS_AVG     210199     68.4
##  8 LIVINGAPARTMENTS_MODE    210199     68.4
##  9 LIVINGAPARTMENTS_MEDI    210199     68.4
## 10 FLOORSMIN_AVG            208642     67.8
## # ... with 112 more rows
```

**application__data have sereral missing values so lets eleminate those columns which have more than 10% missing values.**

```
application_data <- application_data[ lapply( application_data,
                                              function(x) sum(is.na(x)) / length(x) ) < 0.1 ]
miss_var_summary(application_data)
```

```
## # A tibble: 70 x 3
##    variable                 n_miss pct_miss
##    <chr>                     <int>    <dbl>
##  1 OBS_30_CNT_SOCIAL_CIRCLE   1021 0.332
##  2 DEF_30_CNT_SOCIAL_CIRCLE   1021 0.332
##  3 OBS_60_CNT_SOCIAL_CIRCLE   1021 0.332
##  4 DEF_60_CNT_SOCIAL_CIRCLE   1021 0.332
##  5 EXT_SOURCE_2                660 0.215
##  6 AMT_GOODS_PRICE             278 0.0904
##  7 AMT_ANNUITY                  12 0.00390
##  8 CNT_FAM_MEMBERS               2 0.000650
##  9 DAYS_LAST_PHONE_CHANGE        1 0.000325
## 10 SK_ID_CURR                    0 0
## # ... with 60 more rows
```

**lets eleminate the records that have missing values using the below command.**

```
library(tidyr)
application_data <- na.omit(application_data)
miss_var_summary(application_data)
```

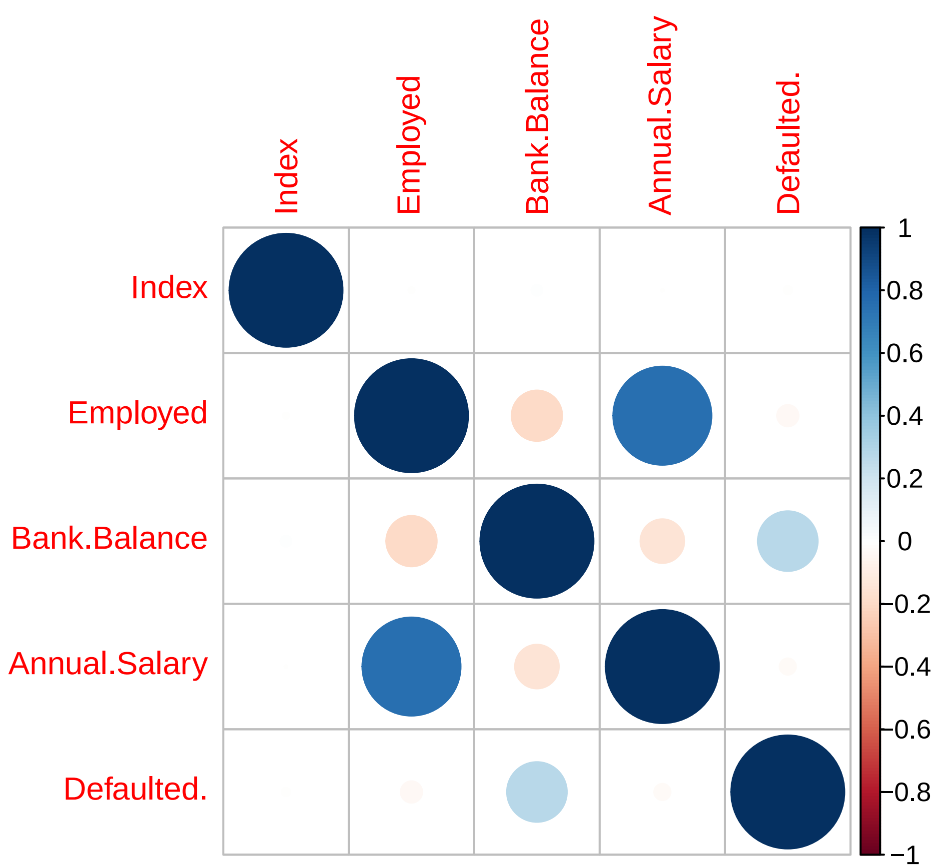
```
## # A tibble: 70 x 3
##    variable           n_miss pct_miss
##    <chr>               <int>    <dbl>
##  1 SK_ID_CURR              0        0
##  2 TARGET                  0        0
##  3 NAME_CONTRACT_TYPE      0        0
##  4 CODE_GENDER             0        0
##  5 FLAG_OWN_CAR            0        0
##  6 FLAG_OWN_REALTY         0        0
##  7 CNT_CHILDREN            0        0
##  8 AMT_INCOME_TOTAL        0        0
##  9 AMT_CREDIT              0        0
## 10 AMT_ANNUITY             0        0
## # ... with 60 more rows
```

**as missing data has been removed from the dataframe we can start analysis. I am using the corrplot to see the correlation matrix.**

```
library(corrplot)
```

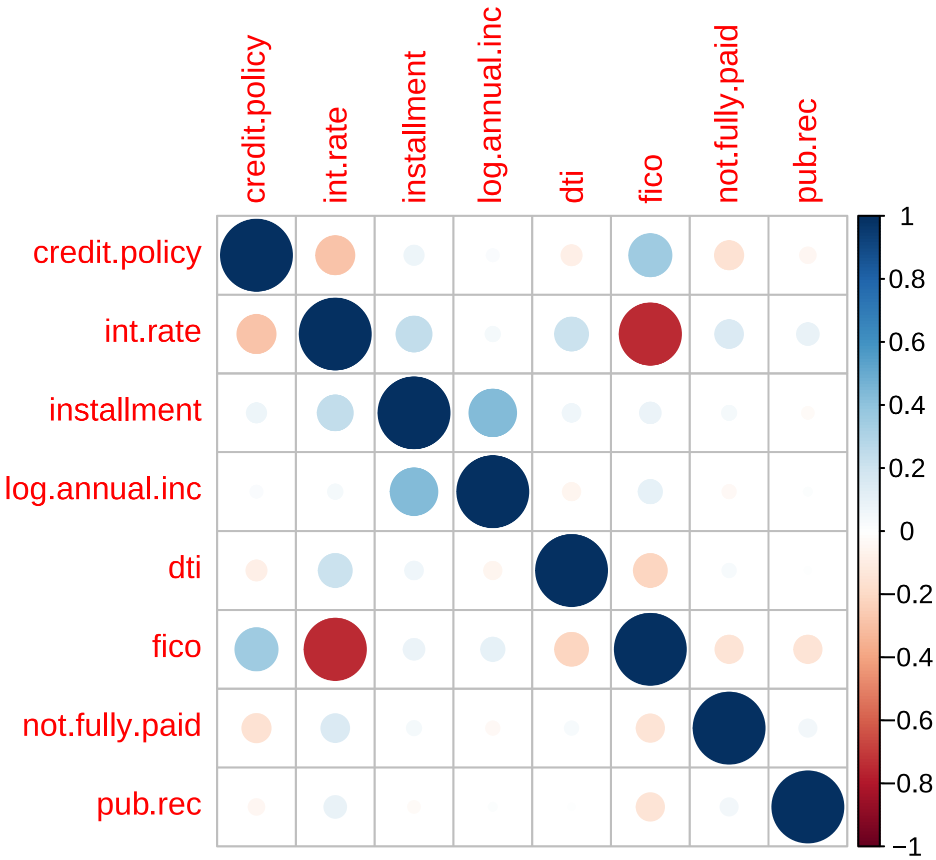
```
## corrplot 0.92 loaded
```

```
corrplot(cor(default_fin, method = c("spearman")))
```



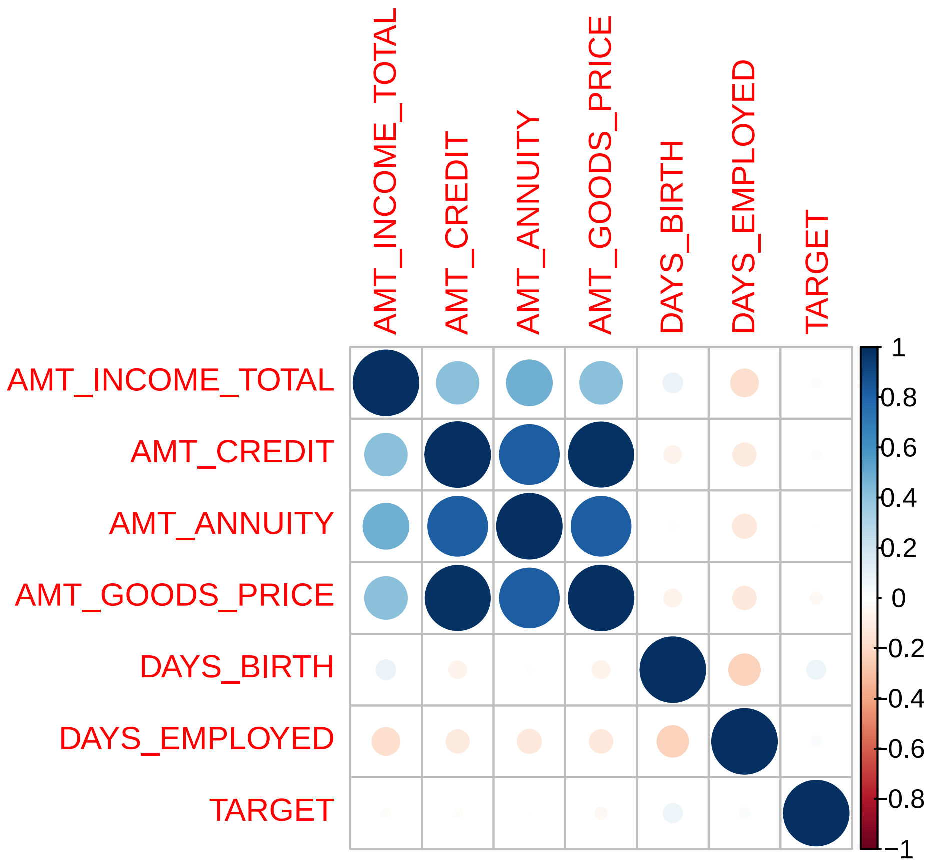
### Looking at the correlation color matrix we can say that defaulters are highly correlated with bank balance.

```
library(corrplot)
corrplot(cor(loan_data[c('credit.policy','int.rate','installment','log.annual.inc','dti','fico','not.ful
```




### From the correlation matrix above there represents the correlation visually, shows not of the attributes have affect on not.fully.paid i.e. defualter.

```
library(corrplot)
corrplot(cor(application_data[c('AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AMT_GOODS_PRICE','DAYS_B
```

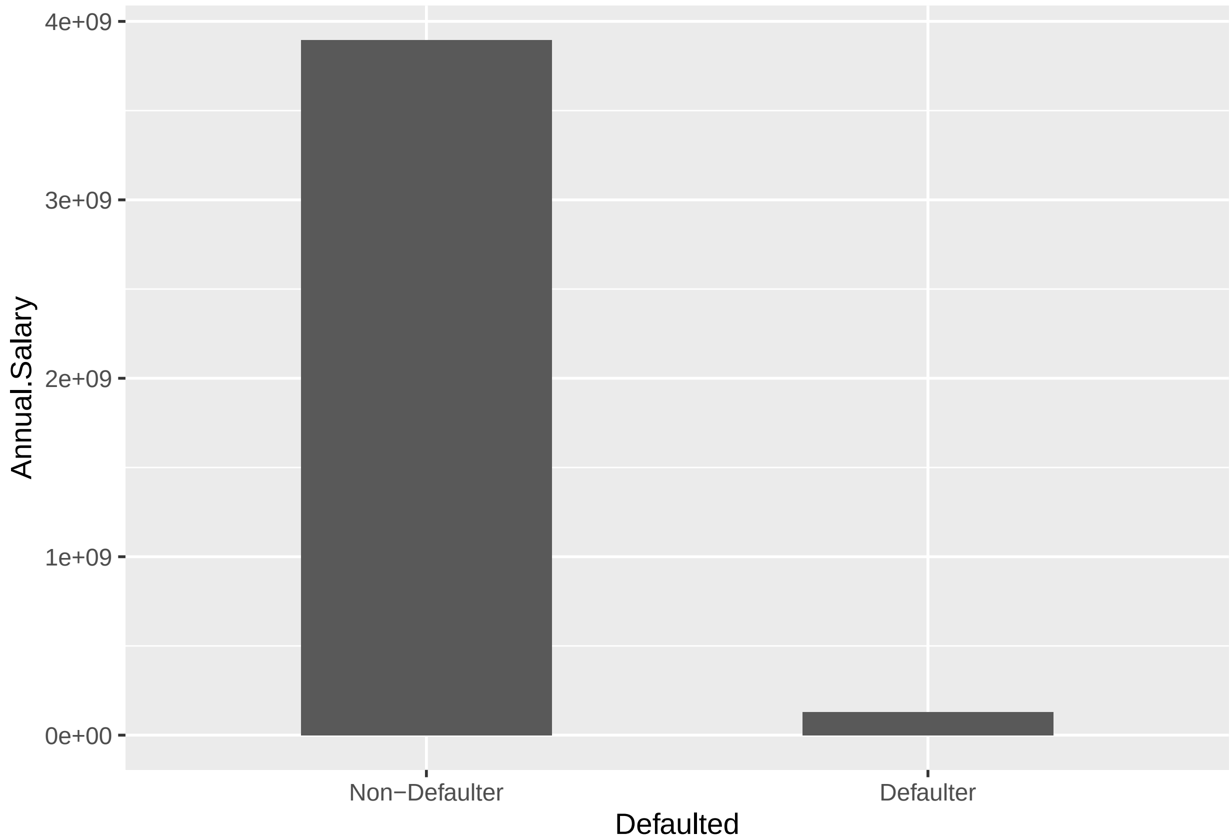



### none of the attributes selected have direct affect on Target fields.

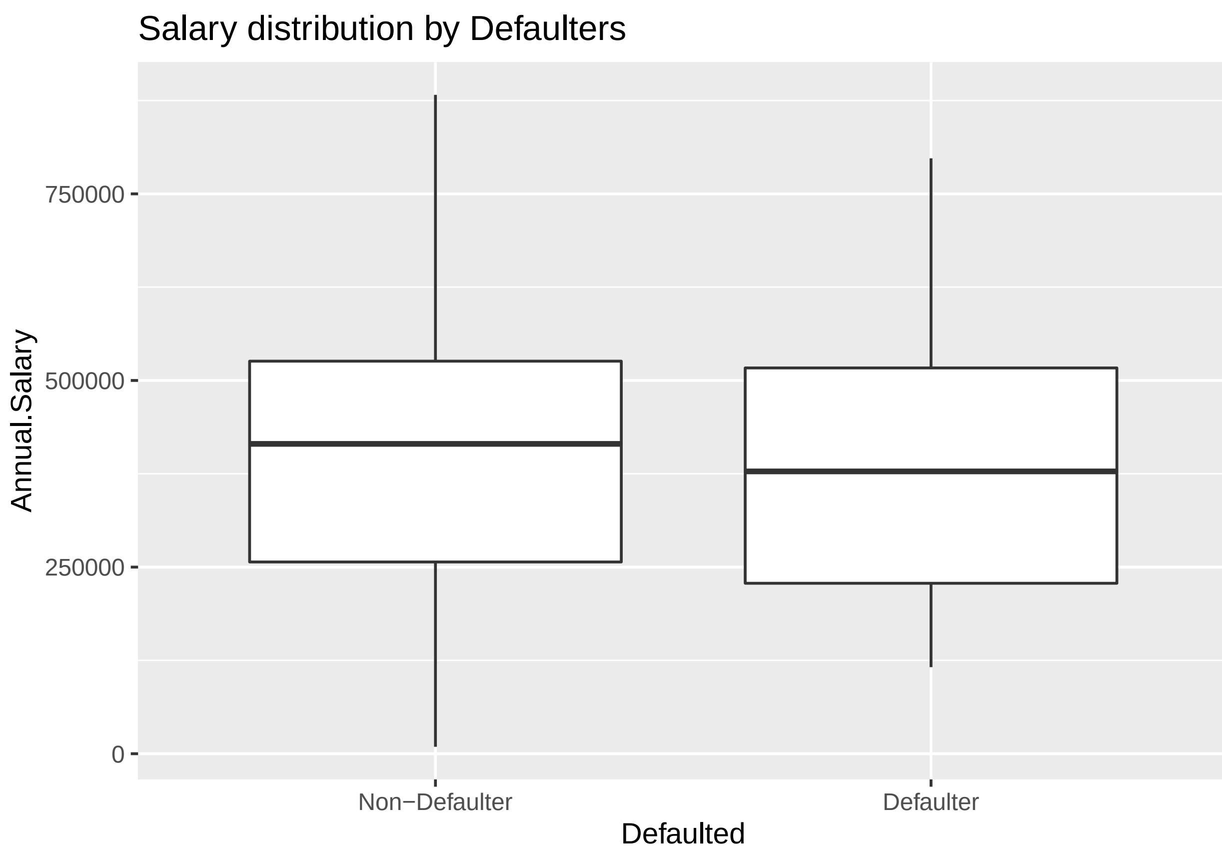
**Is there any relationship there between Income and loan defaulter?**

**Lets plot the bar diagram of defaulter vs annual salary.**

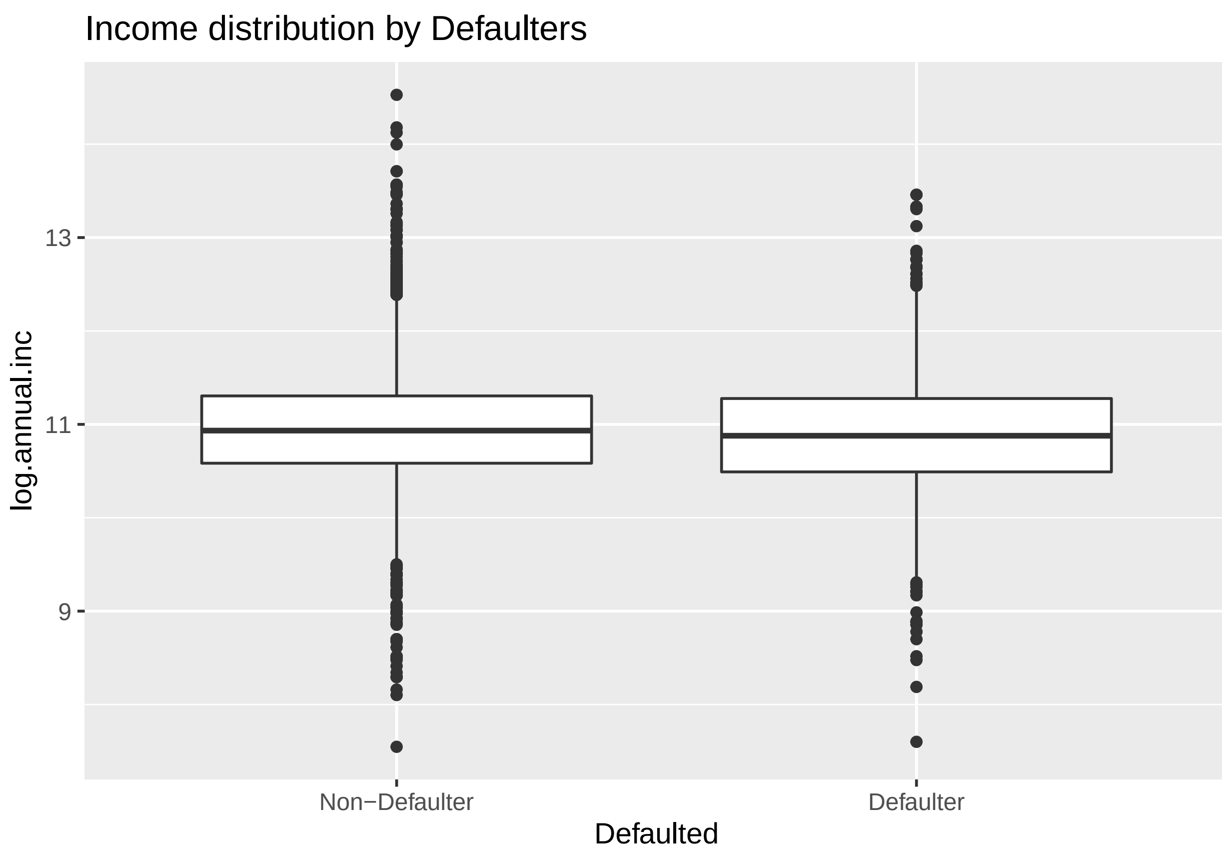
```
library(ggplot2)
default_fin$Defaulted <- factor(default_fin$Defaulted., levels=c(0,1), labels=c("Non-Defaulter","Defaul
loan_data$Defaulted <- factor(loan_data$not.fully.paid, levels=c(0,1), labels=c("Non-Defaulter","Defaul

ggplot(default_fin, aes(x=Defaulted , y=Annual.Salary)) + geom_bar(stat="identity", width=0.5)
```




```
ggplot(default_fin, aes(x=Defaulted , y=Annual.Salary)) + geom_boxplot() + labs(title = "Salary distribu
```




```
ggplot(loan_data, aes(x=Defaulted , y=log.annual.inc)) + geom_boxplot() + labs(title = "Income distribu
```




### The bar chart and box plot clearly says that, the median annual salary for defaulters and non-defaulter around the same range, so its very hard to say if Annaul Salary have effect on being defaulter.

**Lets fit a logistic regression model on defaulter as dependent variable and employment, annual salary and bank-balance as independent variables.**

```
model <- glm(Defaulted. ~ Employed + Annual.Salary + Bank.Balance, data=default_fin, family='binomial')
summary(model)
```

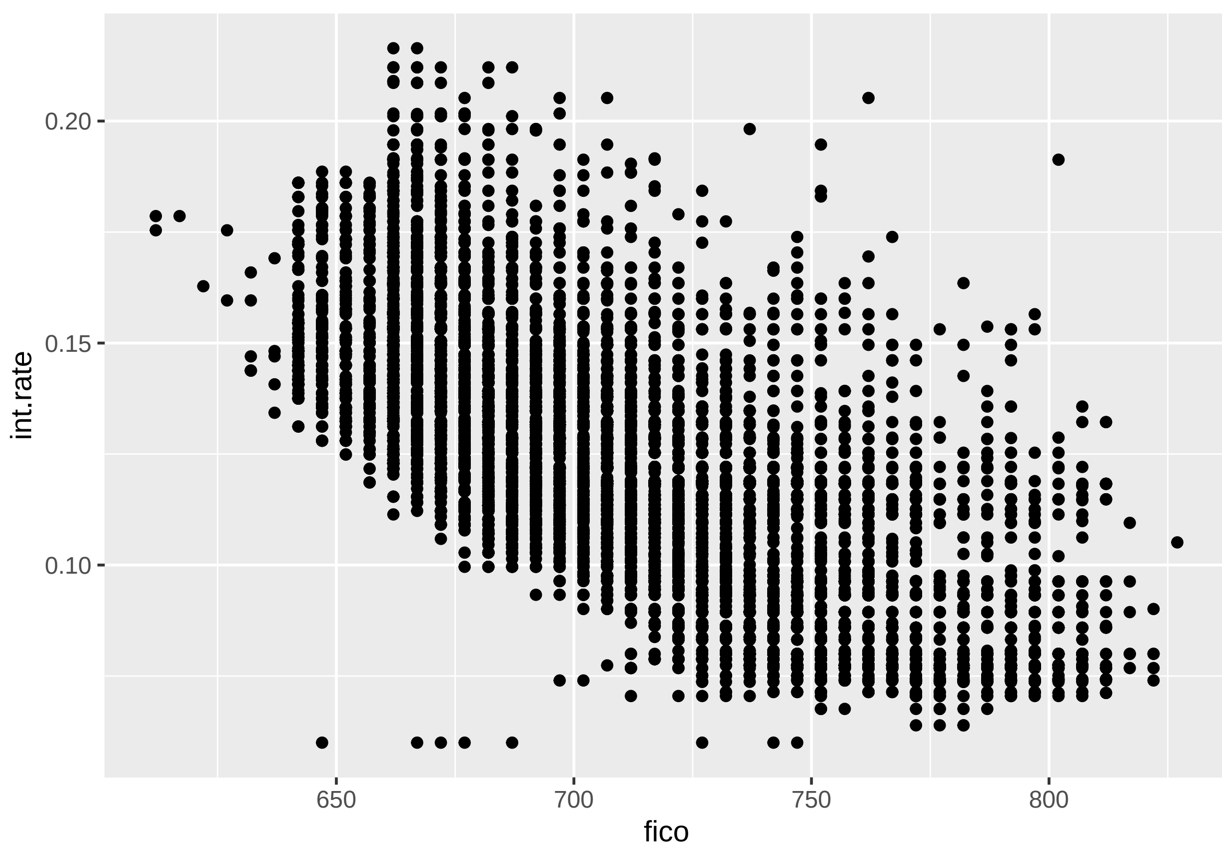
```
##
## Call:
## glm(formula = Defaulted. ~ Employed + Annual.Salary + Bank.Balance,
##     family = "binomial", data = default_fin)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4691  -0.1418  -0.0557  -0.0203   3.7383
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.152e+01  4.379e-01 -26.300  < 2e-16 ***
## Employed       6.468e-01  2.363e-01   2.738  0.00619 **
## Annual.Salary  2.528e-07  6.836e-07   0.370  0.71152
## Bank.Balance   4.780e-04  1.932e-05  24.738  < 2e-16 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2920.6  on 9999  degrees of freedom
## Residual deviance: 1571.5  on 9996  degrees of freedom
## AIC: 1579.5
##
## Number of Fisher Scoring iterations: 8
```

**From the summary of the model, we can see that Bank Balance have significant effect on being defaulter. Also if loan holder has employment or not have some effect on being defaulter, its also quite justified if someone loose the employment its highly likely that loan holder will become a defaulter due of unable to pay the payments, if they dont have enough bank balance. Its also saying the same thing that Annual Salary does not have significant effect on being a defaulter.**

**Lets see how fico and interest rate are related.**

```
ggplot(loan_data, aes(x=fico, y=int.rate)) + geom_point()
```




### As per the scatter plot, we can see if fico is high then interest rate is low. So to get lower interest rate someone need to have high fico score.

## Limitations

**The major limitation for this analysis is data, as we all know defaulter information is very sensitive information, using which we can find someone's economical status, so we cannot use personal identifiable information for this analysis, there are several fields like FICO are quite important and plays important rule for this type of analysis, but we cannot tag PII with that.**

## Remarks

**Though there are some limitations but the 3 data set used from Kaggle are quite good to do analysis and get an overall idea on defaulters. Which this analysis we came to know the how defaulting on loan effected by some of the major attributes, how fico impact on the loan interest rates and how attributes are correlated on loan data.**